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BBA | Semester 6 | UK6DSCMGT301

Research Methodology

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Module 4: Data Analysis and Statistical Inference

Data Preparation, Descriptive and Inferential Statistics, Parametric vs Non-Parametric Tests

Chapter 1: Empirical Data Preparation and Transformation Protocols

1.1 The Imperative of Data Cleaning in Management Research

Empirical business research is only as robust and trustworthy as the integrity of the underlying data from which inferences are drawn. Raw empirical data harvested from online survey engines, field questionnaires, observational logs, or ERP transaction ledgers is inevitably riddled with human omissions, data entry errors, illegible handwriting, contradictory statements, and statistical outliers. If left uncorrected, flawed raw data introduces severe systematic bias into subsequent statistical modeling, distorting regression coefficients, inflating error variances, and producing spurious conclusions that misguide corporate management. Transforming chaotic, unrefined raw field data into a disciplined, structured, and statistically auditable dataset requires four sequential procedures: editing, coding, classification, and tabulation.

1.2 Data Editing: Field Editing versus Central Office Auditing

Data editing is the systematic visual and algorithmic inspection of completed measurement schedules to detect and rectify errors, omissions, illegibilities, and inconsistencies. Editing is executed in two progressive operational tiers:

- **Field Editing:** Conducted by field team supervisors immediately following the completion of an interview or questionnaire administration while the respondent and field investigators remain physically accessible. Field editing detects blatant omissions, clarifies illegible handwriting, deciphers recorded shorthand notes, and verifies that the field investigator followed the designated sampling skip patterns. Field editing must occur on the same day as data collection to prevent recall decay.
- **Central Office Editing:** A comprehensive, centralized audit performed by senior statistical analysts prior to data digitization. Analysts scrutinize the complete dataset for logical consistency across disparate survey items (e.g., ensuring a respondent reporting an age of 19 does not simultaneously claim 25 years of corporate executive experience). Central office editing resolves missing data through standardized protocols:
  - *Listwise Deletion (Complete Case Analysis):* Eliminating any survey record that contains a missing response on any variable under investigation. While simple, listwise deletion can drastically reduce effective sample size and introduce selection bias if data are not missing completely at random (MCAR).
  - *Pairwise Deletion (Available Case Analysis):* Utilizing all available data cases for each specific bivariate calculation, preserving statistical power but generating correlation matrices based on varying sample sizes.
  - *Imputation Techniques:* Replacing missing values using mathematically modeled substitutes, including mean/median substitution, regression imputation, and advanced algorithmic

Expectation-Maximization (EM) or Multiple Imputation (MI) frameworks.

1.3 Data Coding and Codebook Architecture

Data coding is the operational procedure of assigning distinct numerical identifiers, categorical labels, or alphanumeric symbols to raw survey responses to facilitate automated computer processing via statistical packages (such as SPSS, R, Python, or Stata). In modern research workflows, closed-ended questions are pre-coded during the survey design phase (e.g., assigning Gender: Male = 1, Female = 2, Non-Binary = 3; or Likert Agreement: Strongly Disagree = 1 to Strongly Agree = 5). Conversely, open-ended qualitative inquiries require *Post-Coding*: senior researchers conduct content analysis on a representative sample of text narratives, establish mutually exclusive thematic coding categories, and assign standardized numerical values.

A vital deliverable of this phase is the comprehensive **Research Codebook**. The codebook documents the variable name, label, operational question wording, measurement level (nominal, ordinal, interval, ratio), allowable numerical value ranges, missing value definitions, and specific recoding syntax for reverse-scored items. A meticulously maintained codebook guarantees institutional auditability, enables seamless cross-researcher collaboration, and preserves data longevity.

1.4 Data Classification and Tabulation

Classification: The intellectual and computational process of arranging collected data into homogeneous groups or classes according to common characteristics. Classification in business research is executed along four primary dimensions: (a) *Geographical Classification* (grouping by state, district, or sales territory); (b) *Chronological Classification* (arranging data sequentially over quarters, years, or decades); (c) *Qualitative Classification* (grouping by descriptive non-numerical attributes such as industry sector, marital status, or educational attainment); and (d) *Quantitative Classification* (grouping continuous numerical data into discrete class intervals, such as annual turnover tiers or employee age brackets).

Tabulation: The systematic, logical presentation of classified numerical data in structured rows and columns. Tabulation serves three primary analytical functions: (a) it condenses voluminous raw data into an easily interpretable visual matrix; (b) it facilitates immediate comparative evaluation across categories; and (c) it provides the computational foundation for statistical hypothesis testing. Tabulation ranges from *Simple One-Way Frequency Tables* (displaying counts and percentages for a single variable) to *Complex Bivariate and Trivariate Cross-Tabulations (Contingency Tables)*, which analyze the joint distribution of two or more categorical variables simultaneously, forming the empirical basis for Chi-Square tests of independence.

Chapter 2: The Statistical Foundations of Management Analysis

2.1 Descriptive versus Inferential Statistics

Statistical methodology in management research is divided into two foundational domains:

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Descriptive Statistics: Encompasses mathematical and graphical techniques used to organize, summarize, synthesize, and present empirical sample data in a concise, interpretable format. Descriptive statistics focuses exclusively on describing the characteristics of the observed sample without making broader probabilistic generalizations to unobserved populations. The core analytical pillars of descriptive statistics comprise:

- *Measures of Central Tendency:* Quantifying the central location or typical score of a distribution via the Arithmetic Mean ($\bar{X}$), Median (M_d), and Mode (M_o).
- *Measures of Dispersion:* Quantifying the spread, heterogeneity, or variability among observations via the Range, Quartile Deviation, Variance (σ^2 or s^2), Standard Deviation (σ or s), and the dimensionless Coefficient of Variation ($CV = (s/\bar{X}) \cdot 100$).
- *Measures of Distribution Shape:* Evaluating deviations from theoretical symmetry via **Skewness** (quantifying directional asymmetry: positive right-skew vs. negative left-skew) and **Kurtosis** (quantifying peakedness and tail-heaviness: Leptokurtic, Mesokurtic, or Platykurtic distributions).

Inferential Statistics: Involves advanced mathematical techniques that utilize empirical sample data to draw probabilistic inferences, test scientific hypotheses, make predictions, and generalize conclusions regarding the broader, unobserved population parameters. Inferential statistics operates under the mathematical laws of probability theory and is bifurcated into two primary operational branches: **Parameter Estimation** (calculating point estimates and constructing confidence intervals) and **Hypothesis Testing** (determining whether empirical sample differences are statistically significant or merely attributable to random sampling variation).

2.2 The Five-Step Hypothesis Testing Protocol

Scientific hypothesis testing in business administration follows a disciplined, standardized five-step mathematical procedure:

1. **State the Null and Alternative Hypotheses:** Explicitly formulate the null hypothesis (H_0) positing no relationship, no effect, or no difference, and the alternative hypothesis (H_1) specifying the expected research effect.
2. **Establish the Significance Level (α):** Specify the maximum tolerable probability of committing a Type I error. In business management and social science scholarship, α is conventionally set at $0.05 (5% risk) or $0.01 (1% risk).
3. **Select the Appropriate Test Statistic:** Choose the mathematical test (Z-test, Student's t-test, F-test, Chi-Square) based on research design, measurement scale, sample size, and distributional assumptions.
4. **Establish Critical Values and Decision Boundaries:** Determine the statistical rejection region based on degrees of freedom and whether the hypothesis is directional (one-tailed test) or non-directional (two-tailed test). In modern computational analytics, the decision rule evaluates the **p-value (Exact Probability Value)**:
   - If $p \leq \alpha$ \rightarrow **Reject H_0** (Statistically Significant Effect).
   - If $p > \alpha$ \rightarrow **Fail to Reject H_0** (Insufficient Evidence to Support Effect).

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5. **Calculate Test Statistics and State Managerial Implications:** Compute observed test metrics from empirical data, execute the decision rule, and translate statistical outcomes into substantive managerial insights.

2.3 Statistical Decision Errors: Type I and Type II Errors

In testing empirical hypotheses, researchers face the risk of two fundamental decision errors:

Statistical Decision	Null Hypothesis (H_0) is Actually True	Null Hypothesis (H_0) is Actually False
Reject H_0	**Type I Error (α):** False Positive. Rejecting a true null hypothesis. Probability = α (Significance Level).	**Correct Decision:** True Positive. Statistical Power ($1 - \beta$). Correctly identifying a genuine effect.
Fail to Reject H_0	**Correct Decision:** True Negative. Confidence Level ($1 - \alpha$). Correctly concluding no effect exists.	**Type II Error (β):** False Negative. Failing to reject a false null hypothesis. Probability = β.

In management decision-making, the trade-off between Type I and Type II errors carries profound operational consequences. Committing a Type I error in pharmaceutical testing means approving a drug that is actually ineffective or harmful. Conversely, committing a Type II error in venture capital investment means rejecting a disruptive technology startup that would have yielded massive commercial returns. Researchers manipulate sample size n to maximize **Statistical Power ($1 - \beta$)**, aiming for a power threshold of at least 0.80 without inflating Type I error risk.

Chapter 3: Parametric Statistical Analysis in Business Decision-Making

3.1 Mathematical Assumptions of Parametric Tests

Parametric statistical tests make stringent mathematical assumptions regarding the underlying population parameters. Because they utilize all available numerical information (means and variances), parametric tests possess superior statistical power and sensitivity compared to non-parametric alternatives. To legitimately apply parametric tests, empirical data must satisfy four foundational assumptions:

1. **Scale of Measurement:** The dependent variable must be measured on a continuous metric scale—specifically, an interval scale or ratio scale.
2. **Normality of Distribution:** The data in the underlying population must approximate a normal bell-shaped distribution. Researchers verify normality using graphical Q-Q plots, histogram inspections, and formal statistical tests (Shapiro-Wilk test for small samples, Kolmogorov-Smirnov test for large samples). When sample sizes exceed 30 observations per group, the **Central Limit Theorem (CLT)** guarantees that the sampling distribution of the mean approaches normality regardless of population shape.

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3. **Independence of Observations:** Each data observation must be sampled independently, meaning the response of one participant does not influence another.
4. **Homogeneity of Variance (Homoscedasticity):** The variances across the comparison groups must be approximately equal ($\sigma_1^2 \approx \sigma_2^2 \approx \cdots \approx \sigma_k^2$). Verified using Levene's Test of Equality of Variances. If homoscedasticity is violated, researchers apply Welch-Satterthwaite adjusted degrees of freedom.

3.2 Comprehensive Suite of Parametric Tests

The primary parametric tests utilized in management research comprise:

- **One-Sample Z-Test / t-Test:** Compares an observed sample mean against a known or theoretical population benchmark mean (e.g., testing whether an airline's average customer boarding time differs significantly from the industry standard of 20 minutes). If population standard deviation (σ) is known and sample size $n \geq 30$, the Z-test is used; if σ is unknown and estimated from sample standard deviation s, the Student's t-test is applied.
- **Independent Samples Student's t-Test:** Evaluates whether the mean scores of two mutually exclusive, independent groups differ significantly from each other (e.g., comparing quarterly sales productivity between salespeople receiving commission-only compensation versus fixed salary plus bonuses). The test statistic is calculated as:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{s_p^2\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}$$

Where:
$\bar{X}_1, \bar{X}_2$ = Sample means of Group 1 and Group 2.
s_p^2 = Pooled sample variance.
n_1, n_2 = Sample sizes of Group 1 and Group 2.

- **Paired (Dependent) Samples t-Test:** Compares two correlated means obtained from the same group of respondents measured across two distinct chronological time points or experimental conditions (e.g., measuring employee stress levels before and after completing a six-week mindfulness intervention).
- **One-Way Analysis of Variance (ANOVA - F-Test):** Simultaneously evaluates mean differences across three or more independent groups (e.g., comparing customer loyalty scores across four retail bank brands: SBI, HDFC, ICICI, and Axis Bank). Running multiple pairwise t-tests across several groups dramatically inflates the family-wise Type I error rate. ANOVA circumvents this through the omnibus F-test, which partitions total variance into *Between-Group Variance* (explained variance) and *Within-Group Variance* (error/unexplained variance):

$$F = \frac{MS_{between}}{MS_{within}} = \frac{SS_{between}/(k-1)}{SS_{within}/(N-k)}$$

Where:
MS_{between = Mean square between groups.

> MS_{within = Mean square within groups (error variance).
> k = Number of comparison groups.
> N = Total sample size across all groups.

If the omnibus F-test is statistically significant ($p < 0.05$\$), the researcher conducts **Post-Hoc Pairwise Comparisons** (Tukey's HSD or Bonferroni adjustments) to pinpoint exactly which group pairs differ significantly.

- **Pearson Product-Moment Correlation (r):** Quantifies the strength and direction of the linear relationship between two continuous interval or ratio variables, bounded between \$-1.00\$ (perfect negative correlation) and \$+1.00\$ (perfect positive correlation).
- **Ordinary Least Squares (OLS) Linear Regression:** Models the mathematical relationship between one or more independent variables and a continuous dependent variable, estimating predictive beta coefficients (β\$) and the coefficient of determination (R^2\$), which quantifies the percentage of variance explained in the dependent variable.

Chapter 4: Non-Parametric Statistical Analysis in Management Research

4.1 Rationale and Utility of Non-Parametric Methods

Non-parametric statistical tests (often termed *distribution-free tests*) do not rely upon stringent mathematical assumptions regarding the shape or parameters of the underlying population distribution. Non-parametric methods are essential in management research under several common conditions: (a) when the dependent variable is measured on a nominal or ordinal categorical scale (such as customer preference rankings, executive seniority tiers, or Likert scale responses treated ordinally); (b) when sample sizes are small ($n < 30$\$) and population normality cannot be assumed; and (c) when continuous data exhibit extreme outliers, severe skewness, or heteroscedasticity that cannot be rectified through mathematical data transformations (e.g., logarithmic or square-root transformations).

4.2 Dominant Non-Parametric Statistical Tests

Scholars utilize non-parametric tests as direct robust counterparts to classical parametric procedures:

Research Analytical Objective	Parametric Test (Normal Continuous Data)	Non-Parametric Counterpart (Distribution-Free / Ordinal)
Comparing two independent groups	Independent Samples Student's t-test	**Mann-Whitney U Test** (Wilcoxon Rank-Sum Test)
Comparing two paired/related groups	Paired Samples t-test	**Wilcoxon Signed-Rank Test**
Comparing three or more independent groups	One-Way Analysis of Variance (ANOVA F-test)	**Kruskal-Wallis H Test**

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Research Analytical Objective	Parametric Test (Normal Continuous Data)	Non-Parametric Counterpart (Distribution-Free / Ordinal)
Comparing three or more repeated measures	Repeated Measures ANOVA	**Friedman Two-Way ANOVA**
Bivariate association between two variables	Pearson Correlation Coefficient (r)	**Spearman Rank Correlation (ρ)** / Kendall's Tau
Cross-tabulated categorical independence	Log-Linear Modeling	**Chi-Square (χ^2) Test of Independence**

4.3 The Chi-Square (χ^2) Test of Independence

The Chi-Square test of independence is among the most widely utilized non-parametric techniques in marketing, human resources, and business research. It evaluates whether a statistically significant relationship exists between two nominal categorical variables organized within a two-way contingency table (e.g., examining whether consumer brand preference for electric vehicles is independent of geographical region: North, South, East, West). The Chi-Square test statistic compares observed empirical frequencies (O) against theoretical expected frequencies (E) that would occur if the two variables were completely independent:

$$\chi^2 = \sum \frac{(O-E)^2}{E}$$

Where:
O = Observed empirical frequency in a specific contingency cell.
E = Expected frequency for that cell, calculated as: $E = \frac{\text{Row Total} \cdot \text{Column Total}}{\text{Grand Total}}$.
Degrees of Freedom: $df = (r-1) \cdot (c-1)$, where r is the number of rows and c is the number of columns.

To ensure mathematical validity, the Chi-Square test requires that: (a) data represent independent random observations; (b) observations are categorical counts, not percentages or means; and (c) no more than 20% of the cells have expected frequencies less than 5, and no cell has an expected frequency less than 1. For a 2×2 contingency table with small cell counts, researchers apply **Yates' Correction for Continuity** or execute **Fisher's Exact Test**.

Chapter 5: Multivariate Analytical Frameworks and Practical Worked Examples

5.1 Multiple Linear Regression and Econometric Diagnostics

In business research, outcomes are rarely driven by a single factor. **Multiple Linear Regression** examines the simultaneous influence of multiple independent variables ($X_1, X_2, \ldots, X_p$) on a single continuous dependent variable Y:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \epsilon$$

Where:
β_0 = Regression intercept constant.
$\beta_1, \ldots, \beta_p$ = Partial regression coefficients (slopes).
ϵ = Stochastic random disturbance error term.

Rigorous regression analysis requires verification of classical econometric assumptions:

- *Multicollinearity:* High intercorrelations among independent variables inflate standard errors of regression coefficients, making estimates unstable. Verified via the **Variance Inflation Factor (VIF)** and Tolerance ($1/VIF$). A VIF exceeding 5 or 10 indicates severe multicollinearity requiring variable removal or principal component extraction.
- *Homoscedasticity:* Constant error variance across all levels of predicted values. Tested using Breusch-Pagan or White's test.
- *Absence of Autocorrelation:* Residuals must be uncorrelated across observations. Tested using the **Durbin-Watson Statistic (d)**, where values near 2.0 indicate zero serial correlation.

5.2 Factor Analysis and Structural Equation Modeling (SEM)

To reduce large batteries of survey items into a parsimonious set of latent dimensions, researchers deploy **Exploratory Factor Analysis (EFA)**. Suitability of the correlation matrix for factor extraction is evaluated using the **Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy** (acceptable when $KMO \geq 0.70$) and **Bartlett's Test of Sphericity** ($p < 0.001$). Factors are extracted based on Kaiser's criterion (Eigenvalues > 1.0) and Cattell's Scree Plot, followed by orthogonal (Varimax) or oblique (Promax) rotation.

For testing complex, multi-tiered theoretical frameworks, scholars utilize **Structural Equation Modeling (SEM)**. SEM simultaneously evaluates the *Measurement Model* (confirming factor loadings via Confirmatory Factor Analysis) and the *Structural Model* (testing direct, indirect, and total path coefficients). Goodness-of-fit is assessed using standardized fit indices: Comparative Fit Index ($CFI \geq 0.95$), Tucker-Lewis Index ($TLI \geq 0.95$), Root Mean Square Error of Approximation ($RMSEA \leq 0.06$), and Standardized Root Mean Square Residual ($SRMR \leq 0.08$).

5.3 Worked Problem: Chi-Square Test of Independence in Retail Strategy

A retail chain investigates whether customer preference for organic groceries is independent of household income tier. A random sample of 200 shoppers yielded the following contingency table:

Income Category	Prefers Organic (Count)	Prefers Conventional (Count)	Row Total
Low Income	20	60	80
High Income	50	70	120

Income Category	Prefers Organic (Count)	Prefers Conventional (Count)	Row Total
Column Total	**70**	**130**	**Grand Total = 200**

Step 1: Compute Expected Frequencies (E):

- Cell (Low, Organic): $E_{11} = \frac{80 \cdot 70}{200} = 28.0$
- Cell (Low, Conventional): $E_{12} = \frac{80 \cdot 130}{200} = 52.0$
- Cell (High, Organic): $E_{21} = \frac{120 \cdot 70}{200} = 42.0$
- Cell (High, Conventional): $E_{22} = \frac{120 \cdot 130}{200} = 78.0$

Step 2: Calculate the Chi-Square Statistic (χ^2):

$$\chi^2 = \frac{(20-28)^2}{28} + \frac{(60-52)^2}{52} + \frac{(50-42)^2}{42} + \frac{(70-78)^2}{78}$$

$$\chi^2 = \frac{64}{28} + \frac{64}{52} + \frac{64}{42} + \frac{64}{78} = 2.286 + 1.231 + 1.524 + 0.821 = 5.862$$

Degrees of Freedom: $df = (2-1) \cdot (2-1) = 1$.
Critical Value at $\alpha = 0.05$: $\chi^2_{critical} = 3.841$.

Statistical Conclusion: Because the calculated Chi-Square value (5.862) exceeds the critical threshold (3.841), we reject the null hypothesis of independence ($p < 0.05$\$). Customer product preference is statistically significantly associated with household income tier.

Chapter 6: Principles and Protocols of Scientific Data Interpretation

6.1 The Intellectual Nature of Data Interpretation

Data analysis calculates numbers, executes mathematical algorithms, and outputs statistical coefficients; however, data analysis alone does not constitute science. **Data Interpretation** is the vital intellectual process of extracting substantive meaning from statistical outputs, explaining the real-world operational implications of empirical findings, establishing meaningful relationships between observed facts and established theoretical frameworks, and uncovering the underlying causal mechanisms governing business phenomena. Statistical analysis answers the descriptive question of *What occurred?*, whereas data interpretation answers the critical scientific questions of *Why did it occur?* and *What does it mean for corporate strategy?*

6.2 Essential Principles of Rigorous Interpretation

To avoid erroneous generalizations, researchers must adhere to disciplined interpretative principles:

- **Differentiating Statistical Significance from Practical (Managerial) Significance:** A statistical test may yield a statistically significant p-value ($p < 0.001$\$) purely as an artifact of a

massive sample size ($n = 50,000$), even when the observed difference or effect size is minuscule and managerially trivial. Researchers must always report and interpret **Effect Sizes** (e.g., Cohen's d, Partial Eta Squared η_p^2, or standardized regression β) to quantify the practical magnitude of the findings.

- **Avoiding the Fallacy of Equating Correlation with Causation:** Observing a high statistical correlation between two variables does not prove that one variable causes the other. Spurious correlations frequently arise due to common trends or unobserved third variables (confounders). Causal claims must be restricted strictly to randomized experimental designs or established through rigorous longitudinal econometric controls.
- **Theoretical Coherence and Alignment with Literature:** Researchers must critically evaluate empirical results against the foundational literature reviewed in Chapter 2, explicitly explaining whether findings corroborate, refine, or contradict existing theoretical models. Contradictory findings should not be concealed; they represent fertile ground for theoretical innovation.
- **Frank Disclosure of Study Limitations:** Scientific integrity requires transparent disclosure of methodological boundaries, including sample size constraints, geographic boundaries, common method variance risks, and measurement limitations, preventing unjustified overgeneralization.

5.4 Worked Problem 2: Independent Samples Student's t-Test and Cohen's d

A human resource director investigates whether sales representatives trained through immersive virtual reality (VR) simulation achieve higher client acquisition scores than representatives trained via traditional classroom seminars. Random samples from both cohorts yielded the following data:

- Cohort 1 (VR Simulation): Sample size $n1 = 16$, Mean score $\bar{X}1 = 84.5$, Standard deviation $s1 = 6.2$.
- Cohort 2 (Traditional Classroom): Sample size $n_2 = 16$, Mean score $\bar{X}_2 = 78.0$, Standard deviation $s2 = 5.8$.

Step 1: Compute Pooled Sample Variance (s_p^2):

$$s_p^2 = \frac{(n1-1)s1^2+(n_2-1)s2^2}{n1+n_2-2} = \frac{15(6.2)^2+15(5.8)^2}{16+16-2} = \frac{15(38.44)+15(33.64)}{30} = \frac{576.6+504.6}{30} = 36.04$$

Pooled Standard Deviation: $s_p = \sqrt{36.04} \approx 6.003$.

Step 2: Calculate the Student's t-Statistic:

$$t = \frac{\bar{X}1 - \bar{X}2}{\sqrt{s_p^2(\frac{1}{n_1}+\frac{1}{n_2})}} = \frac{84.5-78.0}{\sqrt{36.04(\frac{1}{16}+\frac{1}{16})}} = \frac{6.5}{\sqrt{36.04 \cdot 0.125}} = \frac{6.5}{\sqrt{4.505}} = \frac{6.5}{2.1225} \approx 3.062$$

Degrees of Freedom: $df = n_1 + n_2 - 2 = 30$.
Critical value at $\alpha = 0.05$ (two-tailed): $t_{critical} = 2.042$.
Decision: Because observed t (3.062) exceeds critical t (2.042), reject H_0 ($p < 0.01$). VR-trained representatives exhibit statistically significantly higher sales scores.

Step 3: Calculate Effect Size (Cohen's d):

$$d = \frac{X_1 - X_2}{s_p} = \frac{84.5 - 78.0}{6.003} = \frac{6.5}{6.003} \approx 1.083$$

Interpretation: A Cohen's d of 1.083 represents a *Large Practical Effect Size* (substantially exceeding Cohen's threshold of 0.80), demonstrating that VR training provides immense, substantive operational gains beyond mere statistical significance.

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